Effective Brain Tumor Classification Using Deep Residual Network-Based Transfer Learning

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Abstract *– Brain tumor classification is an essential task in medical image processing that provides assistance to doctors for accurate diagnoses and treatment plans. A Deep Residual Network based Transfer Learning to a fully convoluted Convolutional Neural Network (CNN) is proposed to perform brain tumor classification of Magnetic Resonance Images (MRI) from the BRATS 2020 dataset. The dataset consists of a variety of pre-operative MRI scans to segment integrally varied brain tumors in appearance, shape, and histology, namely gliomas. A Deep Residual Network (ResNet-50) to a fully convoluted CNN is proposed to perform tumor classification from MRI of the BRATS dataset. The 50-layered residual network deeply convolutes the multi-category of tumor images in classification tasks using convolution block and identity block. Limitations such as Limited accuracy and complexity of algorithms in CNN-based ME-Net, and classification issues in YOLOv2 inceptions are resolved by the proposed model in this work. The trained CNN learns boundary and region tasks and extracts successful contextual information from MRI scans with minimal computation cost. The tumor segmentation and classification are performed in one step using a U-Net architecture, which helps retain spatial features of the image. The multimodality fusion is implemented to perform classification and regression tasks by integrating dataset information. The dice scores of the proposed model for Enhanced Tumor (ET), Whole Tumor (WT), and Tumor Core (TC) are 0.88, 0.97, and 0.90 on the BRATS 2020 dataset, and also resulted in 99.94% accuracy, 98.92% sensitivity, 98.63% specificity, and 99.94% precision.*

Keywords*: Brain Tumor Segmentation, Convolutional Neural Network, Deep Residual Network, Magnetic Resonance Images, U-Net Architecture*

1. INTRODUCTION

The segmentation of brain tumors is the phenomenon of detecting the tumor area and the spread of tumor regions like active tumorous tissue, edema tissue, and necrotic tissue. The more complicated deep learning tasks are handled and levels of the tumor presented in the brain are detected by the deep residual networks [1]. A fully convoluted CNN is required to extract features of the whole image and small patches in the segmentation process. The CNN-based ResNet50 framework is used to detect the initial stage of cancer nodes in the classification block and also to identify and classify the tumor in brain images efficiently [2]. Automatic Brain Tumor Segmentation is applied to MRI Images to monitor the improving growth rate of tumors in the brain which makes it simple to improve the survival rate of the patient. Automatic brain tumor segmentation repeatedly identifies the tumor growth and gives quick results [3]. The shape, size and localization of brain tumors are evaluated by multi-modalities without any high ionization radiation effect on patients. A Computer Assisted Diagnosis (CAD) system evaluates the shape of the tumor and landmarks to predict the growth of the tumor and reduce the effect of a brain tumor [4, 5].

The differentiation of brain tumors from normal tumors causes difficulty in brain tumor segmentation and also consists of a high degree in shape, patient extension, and area. To capture the spatial information from far away at different resolutions, a multi-scale 3 Dimensional (3D) U-Nets architecture is used and the 3D depth-wise separable convolution is involved in it to reduce the cost of computation [6]. The image was captured to evaluate the information that existed in it but while capturing the data a lot of noise like pepper noise, salt & speckle noise, and Gaussian noise are reduced by using a modified iterative median filter technique and for input MRI a homomorphic wavelet filter is used [7, 8]. The noise was removed and sent to the inceptionv3 model for extracting the features, where required features are extracted using Non-Dominated Sorting Genetic Algorithm (NSGA). The brain tumor regions are accurately described and the tumor is separated from normal brain tissues by brain tumor segmentation to give the information which is used for treatment planning and diagnosis [9, 10].

The main contribution of the proposed model is evaluated as follows:

- The MRIs are preprocessed initially and performed augmentation to feed the image data to the network for segmentation and classification tasks.
- A Deep Residual Network (ResNet-50) to a fully convoluted CNN is proposed to perform tumor classification from MRI of the BRATS dataset.
- The 50-layered residual network deeply convolutes the multi-category of tumor images in classification tasks using convolution block and identity block.

This research paper includes the related works in Section 2 and Section 3 explains the proposed methodology. The results evaluated by the proposed model are given in Section 4 and Section 5 shows the comparative analysis. The conclusion of this research paper is included in Section 6.

2. RELATED WORKS

Punn and Agarwal [11] presented multi-modalities fusion, tumor extractor, and segmentation to perform tumor segmentation which are the components of a 3D deep neural network. The 3D inception U-net model was used to find the tumor patterns when the extractor component of the tumor moves through the fused images. The necrosis, edema, background, non-enhancing tumor, and enhancing tumor were the target classes used to divide each tumor region into the CT, WT, and ET. Based on the coefficient of dice and index of the Jaccard, the loss function of weighted segmentation was proposed to reduce the problem of class imbalance. The advantages held by using multi-modalities are inception convolutions, segmentation loss function, and 3D U-Net architecture which performed well on BraTS2017 and BraTS2018 datasets. The limitations of multi-modalities did not apply to real-time data fusion, and cascading. Further, it was extended to biomedical image analyses like measuring disease and image registration.

Ullah et al. [12] presented an image quality hypothesis used for the performance of classification in a statistical approach in the preprocessing stage. An updated image technique was used for better results which consist of removing noise using a median filter, contrast enhancement using the histogram equalization technique, and converting the image from grayscale to RGB (red, green, and blue). The Discrete wavelet transform was used to extract the features from MRI and reduced by color moments like mean, skewness, and standard deviation. The MRIs were classified into malignant and benign efficiently using an advanced Deep Neural Network. The drawbacks resulting in it do not apply to larger datasets, including high disease rate, enhancing the image is not performed well, and more time for computation is consumed.

Rehman et al. [13] presented a machine learning technique on Fluid-attenuated Inversion Recovery (FLAIR) scans of MRI. The Gabor filter bank was used for creating text on-map images, bilateral filtering was used for removing the noise and the features were extracted from superpixels. The main advantages of using machine learning techniques were the computational cost of image segmentation was reduced in small regions, and the performance of low-level features was increased by the segmentation of superpixel which was done on texton-map images. The limitations of this work were, stable features and small-size regions were difficult to compute and more time was consumed, difficult to build the model when samples were insufficient and the spatial data was not considered.

Amin et al. [14] presented a fusion process that was used to combine the texture and structural data of four MRI sequences T1, T1C, T2, and Flair when the brain tumor was detected. The process of fusion was done by a Discrete Wavelet Transform (DWT) with Daubechies wavelet kernel, compared to a single sequence of MRI as it provides more information on the tumor region. To remove the noise content a Partial Differential Diffusion Filter (PDDF) and segmentation tumor were detected by a global thresholding method which fed to the proposed CNN model for classifying tumor and non-tumor regions. The fused images give better results and are further extended to other modalities like Positron Emission PET and CT images were analyzed using classified results. The main drawback of using fusion images was the spatial distortion produced affects further processes like classification.

Zhang et al. [15] proposed a mechanism of using multiple encoders in segmenting brain tumors from 3D MRI to address the limitation of implementing 2D images in tumor segmentation. A new loss function has been introduced in this approach to solve the issues of voxel imbalance. The performance measures were evaluated on BRATS 2020 dataset and achieved promising dice scores with better specificity and sensitivity. However, this approach has a limitation of not implementing better data-enhancing techniques and this can be resolved in future by enhancing generalization of the model and preventing overfitting issues.

Sharif et al. [16] proposed a four-phase brain tumor classification model that includes: 1) lesion enhancement, 2) extraction and selection of features for classification using a pre-trained inceptionV3 model and a Non-Dominated Sorted Genetic Algorithm (NSGA), 3) localization using YOLOv2-inception model, and 4) segmentation using McCulloch's Kapur entropy approach. To address the limitation of low prediction rate of brain tumors in existing CNN models that used VGG-16, SVM, and FCM approaches in tumor classification. Three validation datasets namely: BRATS 2018, BRATS 2019, and BRATS 2020 are considered in validating the performance of the proposed model in terms of accuracy, specificity, sensitivity and dice scores. However, this model is not suitable for classifying all types of tumors which is a limitation of this work and this can be resolved by implementing quantum computed algorithms for various brain tumor classification.

Sasank and Venkateswarlu [17] developed a brain tumor segmentation model to address the limitation of the existing Lattice Boltzmann Method (LBM) in tumor segmentation. It was stated that the randomly chosen parameters of LBM affect the performance of the tumor growth model. Hence to overcome this, a Modified Sunflower Optimization (MFSO) based LBM approach was proposed which chooses optimal parameters to improve the tumor growth model's performance. A Scalable Range Adaptive Bilateral Filter (SCRAB) method was used in the pre-processing stage for noise reduction and to improve edges. A fractal and multi-fractal Brownian motion (mBm) method was implemented for feature extraction. The proposed approach was validated on BRATS 2018, BRATS 2019, and BRATS 2020 benchmark datasets and achieved better results with high accuracy, specificity, sensitivity, precision, recall, and F1-score. However, this approach was only employed for segmenting tumor cells in future scan data by referring to the density information of the existing scan data. In the future, effective feature extraction techniques can be implemented in detecting tumor tissues from the first scan point.

Ullah et al. [18] proposed an automatic brain tumor segmentation model that used multiscale residual attention-UNet (MRA-UNet) to overcome the limitations of laborious and time-consuming processes in manual detection of brain tumors. In order to maintain the sequential information, MRA-UNet used three consecutive slices as its input. By using multiscale learning in a cascade way, it was able to make use of the adaptive region of interest scheme and precisely segment enhanced and core tumor regions. This suggested model achieved better dice scores when validated on BraTS2017, BraTS2019, and BraTS2020. However, the proposed model was highly sensitive to noise and also performed over segmentation which is an undesired limitation of this work.

Ullah et al. [19] proposed a Multitask semi-supervised learning framework that used auxiliary tasks for which adequate data was publicly available. To maximize the advantages of multi-task learning, the adversarial autoencoder (AAE) was used, as it has a significant capacity to acquire powerful and discriminative features. Additionally, the semi-supervised learning, which incorporated a discriminative component in an unsupervised AAE training pipeline, was made possible by the coupling of the supervised classification networks with the unsupervised AAE. This method was evaluated using the publicly available COVIDx data and achieved greater accuracy and better generalization ability through a cross dataset validation. However, the proposed model was unstable for training the process which was a limitation of the work.

Solanki et al. [20] suggested a model to detect brain tumors from 2D magnetic resonance images of the brain by utilizing a hybrid deep learning technique. This process is combined with both conventional classification methods and deep learning classification methods such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-layer Perceptron (MLP), Logistic Regression (LR), and Naive Bayes (NB) for performing conventional phase of categorization. The output results demonstrated that SVM produced the most accurate results and later CNN was compared with conventional classifier techniques, which produced significant performance when evaluated on BRATS and MICCAI datasets. Standard investigative methods were not employed to look into the relationship between stroke and brain tumors. It is clear that the conventional system for the diagnosis of brain tumors and strokes lacks automated methods for the identification and segmentation of both brain tumors and strokes.

When samples were insufficient and spatial data was not considered, it was difficult to create the model and took more time. It is challenging to segment brain tumors since they differ from other tumor types to a significant degree in shape, patient extension, and area. The motivation of this work is to develop Deep Residual Network (ResNet-50) to a fully convoluted CNN to perform tumor classification from MRI of the BRATS dataset. The 50-layered residual network deeply convolutes the multi-category of tumor images in classification tasks using convolution block and identity block. A multi-scale 3D U-Nets architecture is also utilized to gather spatial data from distant objects at various resolutions, and the 3D depth-wise separable convolution is integrated into it to lower the computational cost. The summary of the related works is given in Table 1.

To overcome the limitations of existing brain tumor segmentation and classification models, a Deep residual neural network based on transfer learning is proposed in this manuscript for effective brain tumor classification. The proposed model achieves high accuracy by introducing ResNet for tumor classification and also minimizes the problem of vanishing gradient.

Table 1. Summary of Related works

Author	Methodology	Advantages	Limitations
Punn and Agarwal [11]	Multi-modality encoded fusion with 3D inception U-net and decoder model for brain tumor segmentation	The advantages of using multi-modalities are inception convolutions, segmentation loss function, and 3D U-Net architecture and performed well on BraTS2017 and BraTS2018 datasets	More computational time, with a slowed-down pace of learning in the middle of the layers of the network.
Ullah et al. [12]	A hybrid image enhancement-based brain MRI images classification technique	Accurate categorization of malignant and benign classes.	This method is not suitable for larger datasets. Poor Image enhancement and computation time.
Rehman et al. [13]	Texture-based localization of a brain tumor from MRI images by using a machine learning approach	the computational cost of image segmentation was reduced in small regions, and the performance of low-level features was increased by the segmentation of superpixel which was done on texton-map images	Stable features and small size regions were difficult to compute and more time was consumed, difficult to build the model when samples were insufficient and the spatial data was not considered
Amin et al. [14]	Brain tumor classification based on DWT fusion of MRI sequences using convolutional neural network	Spatial degradation and spatial distortions generated in the fused image were reduced.	Shift sensitivity, poor directionality, lack of phase information.
Zhang et al. [15]	ME-Net: a multi-encoder net framework for brain tumor segmentation	This method can well solve the problem of unbalanced foreground and background voxels that often occur in segmentation tasks.	The disadvantage of this method was that it did not consider spatial information and was sensitive to noise and gray-scale unevenness.
Sharif et al. [16]	Active Deep Neural Network Features Selection for Segmentation and Recognition of Brain Tumors using MRI Images	Complex operations are performed simultaneously	High computational time and presence of redundant features.
Sasank and Venkateswarlu [17]	Modified Sunflower Optimization (MFSO) based LBM approach for brain tumor segmentation.	Noise reduction and improved edges	The approach was only employed in segmenting tumor cells in future scan data by referring the density information of existing scan data
Ullah et al. [18]	automatic brain tumor segmentation model that used multiscale residual attention-UNet (MRA-UNet)	This method has an advantage of Less computational cost and simple architecture	highly sensitive to noise and also has over segmentation
Ullah et al. [19]	Multi-task semi-supervised adversarial autoencoding for COVID-19 detection based on chest X-ray images	significant capacity to acquire powerful and discriminative features	The process of training was unstable which resulted in high computational time
Solanki et al. [20]	Detection of brain tumors from 2D magnetic resonance images of the brain by utilizing a hybrid deep learning technique.	It is observed that the 5-layer CNN approach obtains the best outcome compared to the other distributions when it is trained with a learning rate of 0.001, an epoch of 10, and a training duration of 15 secs.	It is clear that the conventional system for the diagnosis of brain tumors and strokes lacks automated methods for the identification and segmentation of both brain tumors and strokes.

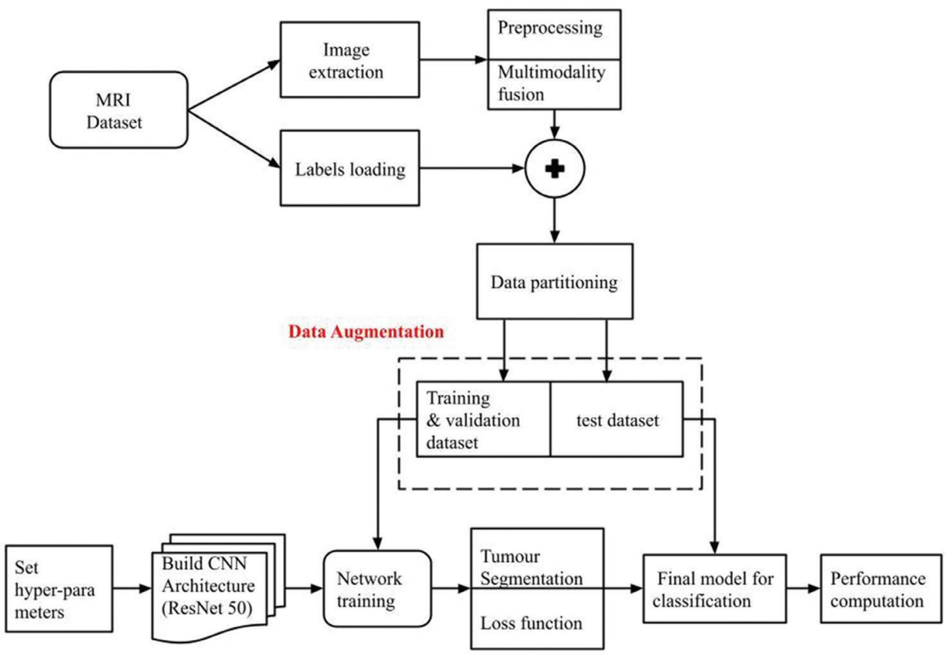

Fig. 1. Block diagram of the proposed model

3. METHODOLOGY

The proposed model for brain tumor segmentation and classification is elaborated in this section by showcasing the block diagram of the proposed architecture. The block diagram shown in Fig. 1 explains the procedure for the classification of MRIs taken from the BRAT 2020 dataset using data preprocessing, data augmentation, CNN-based residual network (ResNet-50), and segmentation.

3.1. DATASET

The BRAT 2020 dataset is considered for pre-processing which consists of MRI out of which 369 images are trained set, validation set consists of 125 images, and 166 images from the test set multimodal brain MRIs of tumor patients having high-grade (undifferentiated tumors) or low-grade (well-differentiated tumors) gliomas are included. Every patient receives T1 & T2 weighted, post-contrast T1 weighted, and FLAIR images. The MRI image has dimensions 240 x 240 x 155, where 155 represents the number of slices. The voxel spacing was the same across all MRI images, at (1 x 1 x 1) mm3. The size of each MRI input image was fixed throughout the process. The dataset includes expert annotation for each subject (i.e. ground fact). FLAIR, T1-Contrast enhanced (T1C), T1, and T2, along with ground truth are the four kinds of MRI modalities. The summary of the BRATS 2020 dataset is shown in Table 2.

Table 2. Summary of BRATS 2020 dataset

Trained set of images	369
Validation set of images	125
Test set of images	166
Types of tumors	Low-grade and high grade
Categories	T1 & T2 weighted, post contrast T1 weighted, and FLAIR images
The MRI image dimensions	240×240×155

3.2. PRE-PROCESSING STAGE

The reduction of original image size for better performance of the network is accomplished by less dimensionality and computations in the image. All of this is involved in the pre-processing stage. MRI images from the BRATS dataset are then extracted by multimodality fusion after labeling the image data as T1, T2, post-contrast T1 weighted, and FLAIR. A Gaussian filter is applied to the image and then finally image data augmentation is performed.

3.2.1. Multi-modalities Fusion

After the data was collected from BRAT 2020 using the filter, each MRI sequence is processed in the inception module (IM), and subsequently, the two sequence concatenation of T1 with T1c and T2 is accomplished with FLAIR resulting in modalities. Preprocessed modality is processed by hierarchical inception blocks instead of using batch axis for direct fusion, which is a multi-modality fusion component. The encoded fused output is then sent to the tumor extractor for deep pattern discovery in the lesion region. The proposed MRI fusion approach is claimed to be effective in improving segmentation outcomes by alternating the architectural designs after extensive tests and the input image is shown in Fig. 2.

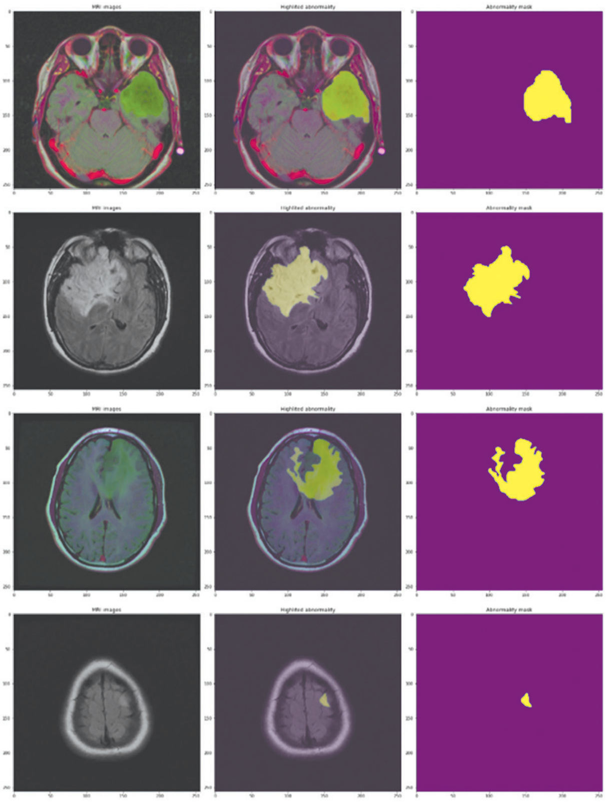

Fig. 2. Input image

3.2.2. Noise removal using a Gaussian filter

The Gaussian filter is one of the most popular filters for noise removal that is majorly used in the pre-processing stage for the detection of brain tumors. The filter removes the noisy data in the MRI scans. The majority of noise reduction techniques do not affect the image sharpness, but the fine details and smoothness across boundaries are reduced in these images by the Gaussian filter. The noise detection with noisy and noise-free images is mathematically represented in Eq. (1)

$$\mathcal{N}(x,y) = \begin{cases} 1, & if\ \mathcal{B}(x,y)\ noisy \\ 0, & if\ \mathcal{B}(x,y)\ noise\ free \end{cases} \quad (1)$$

Where, *N(x,y)* is a noise detection image, and *B(x,y)* is the input image.

After multimodality fusion and labeling the data, the data is filtered to remove noise by using the Gaussian function as shown in Eq. (2)

$$G\ (x,y) = \frac{1}{2\pi\delta^2} e^{-\frac{x^2+y^2}{\delta^2}} \quad (2)$$

Where x and y in the above function represent the location in the Gaussian template.

3.2.3. Data Augmentation

To train the network on unsorted data, the data is shuffled and split into training (80%), and test (20%) datasets. The augmentation technique is applied to the trained dataset to generate new data points and further enhance the model's robustness. Various data augmentation approaches, such as flipping and rotation, are utilized to enable the architecture to understand the variances during training. The degrees or angles for data augmentation flip and rotation methodology are 30, 45, 60, 90, 120, 180, 270, and 360.

3.3. TUMOR SEGMENTATION

After multi-modalities fusion, the segmentation of a brain tumor is processed for separating the tumor from healthy brain tissues. This information is helpful for diagnosis and treatment planning in typical clinical practices. U-Net, which consists of an enlarged up-sampling path for deep feature maps, significantly improves the segmentation performance of medical images. The 3D nature of multimodal MRI poses problems like memory, computation constraints and class imbalance when using the U-Net structure directly in brain tumor segmentation, which is shown in Fig. 3. A path for expanding input images and a skip connection is established to improve segmentation performance that integrates cropped features, and maps from the encoder-decoder network. The residual mapping of adding input features is given by Eq. (3)

$$y(x)=F(x)+x \tag{3}$$

Where $y(x)$ and x are input and output vectors, $F(x)$ is the residual mapping.

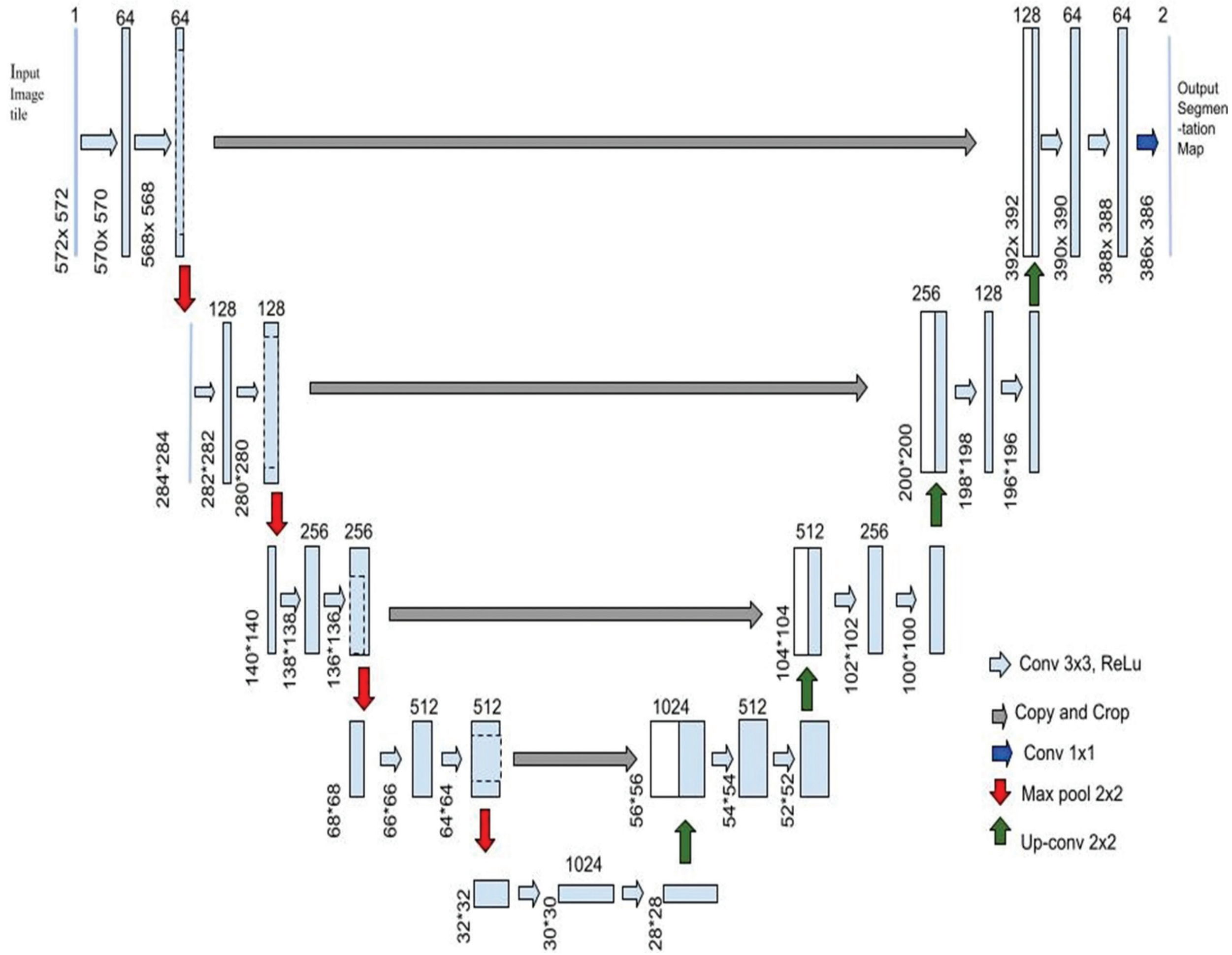

Fig. 3. U-Net architecture

The size of the tumor varies from person to person over time, hence classifying the tumor from various images is a difficult task for radiologists. To extract the features from the MRI images of the trained dataset, the U-Net-based fully convolutional networks were applied. U-Net is used for the quick segmentation process by applying convolutional blocks along with max-pooling to encode the input image into a feature representation. Segmentation using the U-Net model gives high performance in detecting the location and size of the tumor within a lesser time period. The output image of the process is shown in Fig. 4.

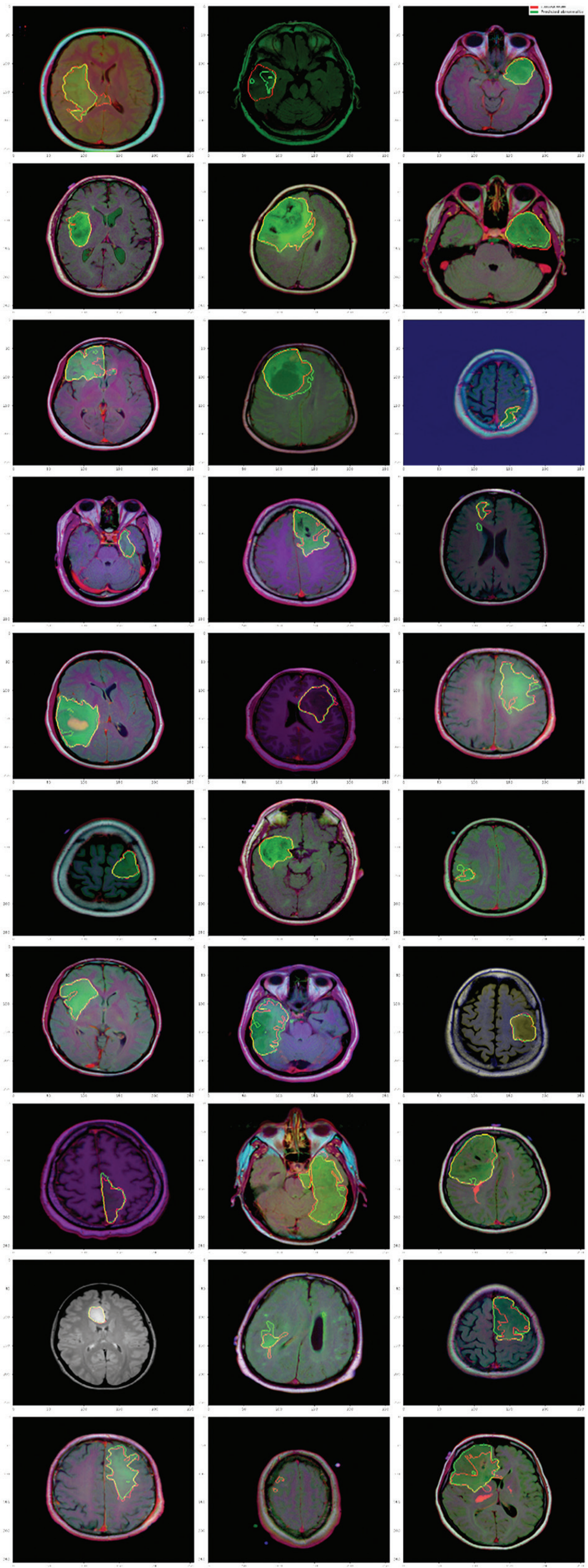

Fig. 4. Output image

3.3.1. Loss Function

The final loss function is a compound loss that is formed as the weighted sum of a few widely used segmentation loss functions. The dice loss is calculated to find the overlap between ground truth values and predicted values.

- **Dice Loss:** Dice loss is the special region-based loss that is used in error reduction that occurs due to overlap of prediction and the ground truth. To use Dice Loss, the Softmax activation function is applied to all pixel values between 0 and 1. Dice loss has the advantage of being able to deal with class imbalance issues very well.

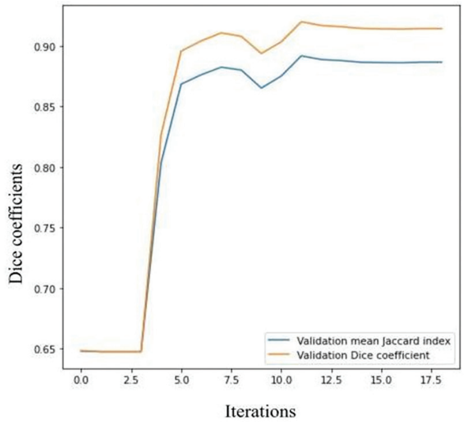

Fig. 5. Dice Loss

- **IoU Loss:** The mismatch error of segmentation is directly optimized in IoU loss. The network's output is given by the probability of a pixel falling into a specific class of the region. The pixel probabilities of output model Y0 for every pixel in the pixel vector are denoted by P and given from 1 to n. The ground truth values are given by $Y_G = [0,1]$ where 0 is the background class and 1 is the object.

To achieve an optimal solution a compound loss function that combines the IoU loss with the Dice Loss and Weighted Cross-entropy loss, is proposed at a faster convergence rate.

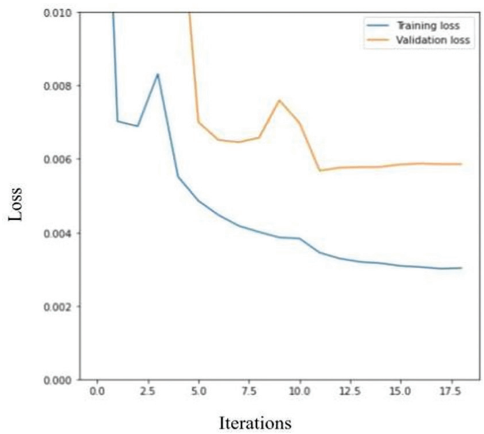

Fig. 6. IoU Loss

3.4. TUMOR CLASSIFICATION USING RESNET-50

After tumor segmentation, the classification involves ResNet with transfer learning. The Residual network (ResNet) is the popular deep network that handles the vanishing gradient problem and uses a learning approach of deep residual to simplify the deeper neural network training and reduce the errors caused by increasing depth, as the network structure is composed of 50 layers. ResNet introduces skip connections, which identify shortcut connections to skip one or more layers. It demonstrates that the model's performance and computational time are directly proportional to the number of layers.

- In transfer learning, a model is trained on a large dataset for one task and then the pre-trained model weights are used to train for another task. Transfer learning improves performance with a simple function that involves adding new fully connected layers to pre-trained models.
- ResNet50 uses identity mapping from previous layers that help in tracking the vanishing gradient. The advantage of residual blocks is that deeper networks can be constructed without increasing the percentage of training error.
- The presence of more layers in ResNet50 help in knowing all the parameters from previous activations in the network, at the same time, solving complex problems, and also improving the overall performance. And more layers are used to retrieve more features from a brain image.

The brain images are classified efficiently to detect the brain tumor while evaluating initial cancer nodules, and this is achieved with high accuracy by using the ResNet50 model in the classification block. The tumor diagnostics were improved by using deep learning techniques without any issues wherein the deep learning increased the training speeds and accuracy. Thus, the proposed model performs brain tumor image classification using ResNet-50 through a transfer learning approach.

4. SIMULATION RESULTS

The proposed approach is implemented with Python 3.6 tensor flow and Keras deep learning platform. All experiments are conducted on a computer with the following specifications: Intel Core (TM) i7-6580 K with 16 GB RAM, frequency of CPU @ 3.360 GHz, and GPU of NVIDIA GeForce GTX 1080. The performance of the proposed model is validated on BRATS 2020 dataset in terms of Accuracy, Sensitivity, and Specificity. The training speed of the developed model is 12 minutes and 54 seconds.

Accuracy:

The test scans use the trained network for overall classification accuracy, which is the ratio of the total of true positives and negatives to the overall prediction trials.

Sensitivity:

The sensitivity metric is used to find a tumor-affected individual. It is the ratio of true positives to the total of true positives and false negatives.

Specificity:

Specificity is the reversal to the sensitivity metric where the test ability finds and designates the individual does not have a tumor. It is the measure of true negatives to the total of true negatives and false positives.

4.1. QUANTITATIVE EVALUATION

In this research, the evaluation of the proposed ResNet-50 DNN architecture is validated on the BRATS-2020 dataset, where it comprises the MRIs of brain tumor patients with different tumor types. To expose the multimodality nature of the SD scans, a U-Net architecture framework is introduced in the network to solve memory computational issues. By validating Table 3 the experimental evaluation is performed by comparing the dice scores of existing models and the proposed models in classifying WT, TC, and ET.

The proposed model achieved better dice scores with WT of 0.97, ET of 0.88, and TC of 0.90 compared to Multi Encoder net for tumor segmentation [21] dice score, WT of 0.88, ET of 0.70, and TC of 0.74. another prior CNN-based model using YOLOv2 inceptionv3 achieved dice scores, WT of 0.93, ET of 0.87, and TC of 0.79.

Table 3. Dice Scores achieved in Tumor Classification on BRATS 2020 dataset

Architecture	Dataset	Dice scores		
		WT	ET	TC
ME-Net [21]	BRATS 2020	0.88	0.70	0.74
YOLOv2 inceptionv3 [22]		0.93	0.87	0.79
Proposed model DNN-based ResNet-50		0.97	0.88	0.90

4.2. COMPARATIVE EVALUATION

The comparative analysis between the proposed model and the prior models is given in Table 4. The performance metrics accuracy, sensitivity, and specificity of prior models with the proposed model are compared in this section. A CNN-based ME-net model has achieved an accuracy of in the region of WT, sensitivity of 91.30%, and specificity of 96.73%. Another CNN-based model using YOLOv2 inceptionv3 model has achieved an accuracy of 98.52%, sensitivity of 98.78%, and specificity of 97.29%. The deep residual model achieved an accuracy of 99.94%, a sensitivity of 98.92%, specificity of 98.63% which are higher than the other two CNN-based models. The proposed Deep Residual Network overcomes the limitations of existing models such as multi-modality fusion, more vanishing gradient, and low-performance feature extraction.

The advantage of the proposed model is; it performs pre-processed modality using hierarchical inception blocks for direct fusion, and decreases vanishing gradient by using ResNet-50, because the network finds skip connections, which identify shortcut connections to skip one or more layers [23, 24]. The overfitting of the model can be overcome by using the 50-layered residual network that deeply convolutes the multi-category of tumor images in classification tasks using convolution block and identity block [25, 26].

Table 4. Performance Metrics of Proposed Model

Architecture	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
CNN-based ME-Net model		97.46	91.30	96.73
CNN-based YOLOv2 inceptionv3	BRATS 2020	98.52	98.78	97.29
DNN-based ResNet-50 model		99.94	98.92	98.63

5. CONCLUSION

The deep residual networks improved the accuracy and training time was reduced to enhance the performance of the residual networks. The ability of deep residual networks reduced the problem of vanishing gradient. The CNN with ResNet-50 model consists of 50 layers to predict the tumor in the brain images where the input is taken from a pre-trained network that trains a million images from the ImageNet database. The 2020 BRATS dataset includes 369 images of the training set, 125 validation sets, and 166 test sets of multimodal brain MRIs of patients consisting of high-grade or low-grade gliomas. The Gaussian filter and data augmentation are used in preprocessing to remove the noise and after multi-modalities fusion, the tumor was separated from healthy brain tissue which helps with diagnosis and treatment planning. Transfer learning is used for classification with ResNet after segmentation and a popular deep network reduces the problem of vanishing gradient and the dice score resulted as 0.88 for enhanced tumor, 0.97 for detecting the whole tumor, and 0.90 for tumor core on the validation set. In future work, transfer learning can be implemented in large datasets and detect various types of tumors in the early stages.

Nomenclature

Parameters	Representation
x	Horizontal orientation in Gaussian template
y	Vertical orientation in Gaussian template
L_F	Loss function
L_{iou}	Loss of Intersection over Union
L_{Dice}	Dice loss
N	Sample set
L	Label set
y_i^l	Sampling encoder
$\hat{y}_i^{(l)}$	Predicted probability
ϵ	constant
Y_0	Output model
P	Pixel vector
Y_G^p	Pixel vector of ground truth values
Y_0^p	pixel values of output model

6. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

7. AUTHOR CONTRIBUTIONS

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, and visualization, have been done by 1st author. The supervision and project administration, have been done by the 2nd author.

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